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Title:

Telecommunications energy and greenhouse gas emissions management for future network growth

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Five highlights:

- Model to evaluate key interdependencies of a fast growing telecommunications network.
- Network growth analysis using real data and Monte Carlo simulation.
- Importance of both operational and embodied energy efficiency improvements.
- Embodied energy expected to dominate in the future under current energy efficiency trends.
- Carbon footprint and energy management through optimum network replacement cycle.

Keywords: Telecommunications network; Network growth; Energy efficiency; Operational energy; Embodied energy; Network replacement cycle

Abstract:

A key aspect of greener network deployment is how to achieve sustainable growth of a telecommunications network, both in terms of operational and embodied energy. Hence, in this paper we investigate how the overall energy consumption and greenhouse gas emissions of a fast growing telecommunications network can be minimized. Due to the complexities in modeling the embodied energy of networks, this aspect of energy consumption has received limited attention by network operators. Here, we present the first model to evaluate the interdependencies of the four main contributing factors in managing the sustainable growth of a telecommunications network: (i) the network's operational energy consumption; (ii) the embodied energy of network equipment; (iii) network traffic growth; and (iv) the expected energy efficiency improvements in both the operational and embodied phases. Using Monte-Carlo techniques with real network data, our results demonstrate that under the current trends in overall energy efficiency improvements the network embodied energy will account for over 40% of the total network energy in 2025 compared to 20% in 2015. Further, we find that the optimum equipment replacement cycle, which will result in the lowest total network life cycle energy, is directly dependent on the technological progress in energy efficiency improvements of both operational and embodied phases. Our model and analysis highlight the need for a comprehensive approach to better understand the interactions between network growth, technological progress, equipment replacement lifetime, energy consumption, and the resulting carbon footprint.

1. Introduction

The amount of data carried by telecommunication networks is expected to continue to grow over the next decade at a rate of 25% to 45% per year [1, 2] and the network operational energy consumption is expected to increase at an annual rate of 10% [3, 4]. In recent years, scientists and researchers have dedicated significant research efforts to quantifying and managing the energy consumed by telecommunication networks. Current research on improving network energy efficiency is divided into two major themes: (a) operational energy efficiency, which aims to reduce the energy used in operating network equipment and devices [5-9] and (b) embodied energy efficiency, which aims to better manage the energy used in raw material acquisition and pre-processing, production, distribution, and end-of-life treatment of network equipment and devices [10-12]. However, both operational and embodied energy efficiency improvements should be jointly considered when managing the energy consumption of a rapidly growing telecommunications network because they are strongly related [8, 13]. For example, *to benefit from the technological progress that improves the operational energy efficiency of network equipment requires network operators to frequently replace network equipment to realize operational energy savings. However, replacing network equipment frequently requires the production of new network equipment units and the disposal of outdated equipment, thereby increasing the embodied energy consumption of the network.*

Balancing the operational and embodied energy that is required is also critical in managing the sustainable expansion of a rapidly growing network. The problem of balancing operational energy and embodied energy is also critical in other areas such as batteries used in electric vehicles [14] and the production and usage of emissions-free power plants [15]. In this paper, the sustainable growth of a network is taken to mean a growth strategy that minimizes the overall energy footprint of the network. This will provide the greatest opportunity for the network to grow in response to increasing demand for services in the longer term as the constraints on growth become more stringent due to resource depletion. Here, we focus on determining the optimal approach to network growth when accounting for the environmental (life cycle energy and greenhouse gas emissions) impact and the economic cost of the network growth. By minimizing the overall energy cost of the network, the optimal approach developed in this paper will also enhance the availability of services to populations who may not currently have access to digital services. As economic growth becomes more constrained by resource depletion, the provision of digital services in developing nations will need to recognize these constraints. Approaches similar to that described in this paper will provide the best opportunity to extend these services to emerging economies.

Managing the sustainable growth of telecommunication networks requires careful consideration of four factors [13]: (i) the operational energy consumption of the network infrastructure; (ii) the embodied energy consumption required for network expansion and equipment renewal; (iii) the network traffic growth rate; and (iv) the technological progress in both operational and embodied energy efficiency improvements. Analyses have considered the interactions between (i) and (ii) [8, 16], (ii) and (iv) [11,12,17,18], and (i), (iii), and (iv) [5-7,19]. However, *no analyses have been conducted to understand the interdependencies among all four factors in the sustainable growth of a network*.

In Section 2, we propose a new model, which can be used to evaluate the interdependencies of (i), (ii), (iii), and (iv) for better managing the life-cycle energy consumption and the resulting greenhouse gas emissions of a rapidly growing network. Without loss of generality, we use an example of a state-wide research and education network, i.e., the California Research and Education Network – CalREN, as the application focus for our energy model. However, the general model that we have developed can be applied to a wide range of different types of telecommunication networks. In Section 2, a critical assessment of the uncertainty in current trends of energy efficiency improvement (in both operational and embodied phases) is performed. The use of the Monte Carlo approach to deal with the uncertainty in parameters is also explained. In Section 3, we present the following analysis to understand the key interdependency factors in reducing the total network energy consumption to meet future network traffic growth. First, the results give insights into the rate of growth in the total life cycle energy of a growing network under current trends in energy efficiency improvements. Second, because network traffic growth is one of the main contributing factors in network deployment, we examine the impact of different network traffic growth rates to the total life-cycle energy of a network. To minimize the total life cycle energy of a network, the network operator has to make a decision on replacing legacy equipment with more energy-efficient equipment to gain network operational energy efficiency improvements. However, rapid replacement of network equipment units could potentially increase the network's embodied energy. Therefore, to help network operator in making an optimum decision of when to replace their network equipment, we investigate the impacts of energy efficiency improvements on the network equipment replacement strategy. Finally, Section 4 presents the conclusion of the paper.

2. Methods for managing the energy consumption of telecommunication networks

The total network energy consumption in year τ, $E_{total}^{(\tau)}$, is the sum of both network operational energy consumption ($E_{network}^{(\tau)}$) and the network embodied energy due to network deployment ($E_{embodied}^{(\tau)}$) in year τ: $E_{total}^{(\tau)} = E_{network}^{(\tau)} + E_{embodied}^{(\tau)}$.

2.1. Operating energy efficiency of a network

The network operating energy ($E_{network}$) is the integral of the total network power consumption over the duration of use (D):

$$E_{network}(D) = \int_0^D \left(P_{equipment}(t) + P_{overheads}(t)\right) dt, \qquad (1)$$

The total network operational power consumption consists of two components: the power consumption in operating network equipment that carries network traffic ($P_{equipment}$), and the power consumption in the overheads ($P_{overheads}$) that support normal network equipment operation (i.e., cooling network equipment, power distribution losses, and other overheads). Typical network equipment will consume a fixed offset power P_{base} when the network equipment has no traffic to process [20]. Beyond P_{base}, the power consumption of typical network equipment has an approximately linear dependence on the amount of data carried by the unit (in bits per second) [20]. Therefore, we assume that the power consumption of a network has a similar dependence on the amount of data carried by the network. As a result, the total network equipment power will take the following form:

$$P_{equipment}(t) = P_{base} + (P_{max} - P_{base}) \times \left(\frac{T(t)}{T_{max}}\right), \tag{2}$$

where P_{max} is the maximum network equipment power that occurs when the network traffic T is operating at its maximum load T_{max}. Inserting the equation for $P_{equipment}$ into Eq. (1) and implementing the integral gives the total equipment energy consumption over duration D:

$$\int_0^D P_{equipment} dt = P_{base}D + \frac{(P_{max} - P_{base})}{T_{max}} T_{ave}D = P_{equip,ave}D, \tag{3}$$

where T_{ave} is the average traffic through the equipment given by $\int_0^D T dt \,/D$. The overheads are either constant or are approximately linearly dependent upon the equipment power given by the power usage effectiveness (PUE), defined as the ratio of the total power required for operating a network to the power used only by the network equipment [5]. Therefore, the equation can be simplified to the following:

$$E_{network}(D) \approx \left(P_{equip,ave} + P_{o/h,ave}\right) \times D, \tag{4}$$

where $P_{o/h,ave}$ is the yearly averaged overhead power when D is one year.

The network operational energy efficiency ($\eta_{equipment}$) is a widely used concept for comparing the energy efficiency of equipment and networks [21]. This parameter is typically defined as the ratio of the total (network) operating energy, $P_{equip,ave} \cdot D$ (in joules) to the total network traffic $T_{ave} \cdot D$ (in bits) carried by the network over a duration D:

$$\eta_{equipment} = \frac{\left(P_{equip,ave} + P_{o/h,ave}\right)D}{T_{ave}D}. \tag{5}$$

Inserting Eq. (3) into Eq. (5), $\eta_{equipment}$ now becomes:

$$\begin{aligned}
\eta_{equipment} &= \frac{P_{equip,ave}}{T_{ave}} + \frac{P_{o/h,ave}}{T_{ave}} \\
&= \frac{\left(P_{base} + \frac{(P_{max} - P_{base})}{T_{max}} T_{ave}\right)}{T_{ave}} + \frac{P_{o/h,ave}}{T_{ave}} \\
&= \frac{P_{base}}{T_{ave}} + \frac{(P_{max} - P_{base})}{T_{max}} + \frac{P_{o/h,ave}}{T_{ave}}.
\end{aligned} \tag{6}$$

Introducing the network proportionality parameter $r = P_{base}/P_{max}$ and utilization $u = T_{ave}/T_{max}$, Eq. (6) now becomes:

$$\begin{aligned}
\eta_{equipment} &= \frac{rP_{max}}{uT_{max}} + \frac{P_{max}}{T_{max}} - \frac{rP_{max}}{T_{max}} + \frac{P_{o/h,ave}}{T_{ave}} \\
&= \left(\frac{P_{max}}{T_{max}}\right)\left\{\left(\frac{r}{u}\right) + 1 - r\right\} + \frac{P_{o/h,ave}}{T_{ave}}.
\end{aligned} \tag{7}$$

There are four ways to improve $\eta_{equipment}$: (i) reduce the yearly average overhead power ($P_{o/h,ave}$), (ii) reduce the network equipment ratios (P_{max}/T_{max}), (iii) reduce the network idle power thereby making the network more load proportional (which corresponds to $r \rightarrow 0$), and (iv) increase network utilization u. It should be noted that the network operator decides the parameter u based on specific network traffic profiles and customer requirements. A greater increase in peak traffic compared with average traffic has been forecasted by [2]. Therefore, assuming that all of the network equipment is powered on 24/7 and assuming the continuation of the practice of dimensioning the network for peak load, we would expect the parameter u for global traffic to decrease each year.

We define the annual fractional reduction, α, of the parameter Y between year τ and τ+1 as:

$$\alpha = \frac{Y^{(\tau)} - Y^{(\tau+1)}}{Y^{(\tau)}}. \tag{8}$$

Using this, we define $\alpha_{o/h}$, α_{max}, and α_{base} as the annual fractional reductions of $P_{o/h,ave}$, (P_{max}/T_{max}), and (P_{base}/P_{max}), respectively, which come about from improvements in technology:

(i) reduction in $P_{o/h,ave}$: $\alpha_{o/h}$,

(ii) reduction in (P_{max}/T_{max}): α_{max},

(iii) reduction in (P_{base}/P_{max}) or r: α_{base}.

For example, $P_{o/h,ave}$ for year τ, ($P_{o/h,ave}^{(\tau)}$), can be determined based on the annual reduction information from the previous year:

$$P_{o/h,ave}^{(\tau)} = \left(1 - \alpha_{o/h}\right) P_{o/h,ave}^{(\tau-1)}. \tag{9}$$

Similarly, $\left(\frac{P_{max}}{T_{max}}\right)^{(\tau)}$ and $r^{(\tau)}$ can be determined using Eq. (10) and Eq. (11), respectively:

$$\left(\frac{P_{max}}{T_{max}}\right)^{(\tau)} = (1 - \alpha_{max}) \frac{P_{max}^{(\tau-1)}}{T_{max}^{(\tau-1)}}, \tag{10}$$

$$r^{(\tau)} = 1 - (1 - \alpha_{base}) r^{(\tau-1)}. \tag{11}$$

By including Eq. (9), Eq. (10), and Eq. (11) into Eq. (7) and then converting to Eq. (4) by multiplying $\eta_{equipment}$ with (T_{ave}), the average operating energy consumption of the network equipment in year τ, $E_{network}^{(\tau)}(D)$, can then be determined using Eq. (12):

$$E_{network}^{(\tau)}(D) \approx \left[\left((1 - \alpha_{max}) \frac{P_{max}^{(\tau-1)}}{T_{max}^{(\tau-1)}} \right) \left\{ \left(1 - (1 - \alpha_{base}) r^{(\tau-1)}\right) + \left(\frac{(1 - \alpha_{base}) r^{(\tau-1)}}{u^{(\tau)}} \right) \right\} T_{ave}^{(\tau)} + \left(1 - \alpha_{o/h}\right) P_{o/h,ave}^{(\tau-1)} \right] \times D \tag{12}$$

It should be noted that Eq. (12) assumes that the energy efficiency improvement factors are the same for all types of equipment in the network. However, different classes of equipment could experience different energy efficiency improvements due to different energy profiles and functionalities. In other words, Eqs. (9), (10), and (11) are dependent on the equipment class, *k* (e.g., small chassis router, large chassis router, small chassis switch, large chassis switch, etc.). Therefore, Eq. (12) can be expanded into *l* different classes of equipment:

$$E_{network}^{(\tau)}(D) \approx \left[\sum_{k=1}^{l}\left[\left((1-\alpha_{max})\frac{P_{k,max}^{(\tau-1)}}{T_{k,max}^{(\tau-1)}}\right)\left\{\left(1-(1-\alpha_{base})r_k^{(\tau-1)}\right) + \left(\frac{(1-\alpha_{base})r_k^{(\tau-1)}}{u_k^{(\tau)}}\right)\right\}T_{k,ave}^{(\tau)}\right] + \left\{(1-\alpha_{o/h})P_{o/h,ave}^{(\tau-1)}\right\}\right] \times D, \tag{13}$$

where *k* represents each class of equipment in the network. It should be noted that equipment capacity is deployed based on peak traffic rather than average traffic. Therefore, the difference between the average traffic growth rate and peak traffic growth needs to be included in the parameter $u^{(\tau)}$ for both the operational and the embodied energy calculations.

2.2. Embodied energy efficiency of a network

Adopting similar approach as in [22], we define the embodied energy efficiency for *k*-class equipment, $\eta_{k,embodied}$ as the embodied energy required, $E_{k,emb}$, for producing, deploying and decommissioning a network element with maximum capacity $T_{k,max}$.

$$\eta_{k,embodied} = \frac{E_{k,emb}}{T_{k,max}}. \tag{14}$$

Embodied energy efficiency, $\eta_{k,embodied}$, has the units of Joules/(bits per second).

The total network embodied energy of the equipment units deployed in year τ ($E_{embodied}^{(\tau)}$) due to the replacement of legacy equipment and the deployment of new network equipment units is:

$$E_{embodied}^{(\tau)} = \sum_{k=1}^{l} E_{k,embodied}^{(\tau)}, \tag{15}$$

If the embodied energy efficiency of the network equipment produced in year τ, required to handle a given network capacity, is known, the total embodied energy of the k^{th} class of equipment deployed in year τ, $E_{k,embodied}^{(\tau)}$, can be determined using the following equation:

$$E_{k,embodied}^{(\tau)} = \left(\eta_{k,embodied}\right)^{(\tau)} \times \left(T_{k,max,new}^{(\tau)} + T_{k,max,replace}^{(\tau)}\right), \tag{16}$$

where the term $\left(\eta_{k,embodied}\right)^{(\tau)}$ is the embodied energy efficiency of the network equipment deployed in year τ and designed to handle a network capacity of $T_{k,max}$ in year τ. $T_{k,max,new}^{(\tau)}$ is the total amount of new network capacity required to handle new traffic (in bits-per-second) in year τ, and $T_{k,max,replace}^{(\tau)}$ is the total amount of new network capacity required to handle the network traffic (in bits-per-second) carried by old equipment units that are to be replaced at year τ. It should be noted that both $T_{k,max,new}^{(\tau)}$ and $T_{k,max,replace}^{(\tau)}$ are the network capacities to be deployed based on peak traffic.

If the information on $\left(\eta_{k,embodied}\right)^{(\tau)}$ is unavailable, an alternate way to determine $E_{k,embodied}^{(\tau)}$ is to estimate the annual reduction in embodied energy efficiency of each class of equipment ($\alpha_{k,emb}$). Hence, we estimate the embodied energy efficiency of each class of equipment in year τ based on the data for 2015:

$$E_{k,embodied}^{(\tau)} = \left(1 - \alpha_{k,emb}\right)^{(\tau-2015)} \left(\eta_{k,embodied}\right)^{(2015)} \times \left(T_{k,max,new}^{(\tau)} + T_{k,max,replace}^{(\tau)}\right). \tag{17}$$

The term $\left(\eta_{k,embodied}\right)^{(2015)}$ represents the embodied energy efficiency in the year 2015, where $\left(\eta_{k,embodied}\right)^{(2015)} = \left(P_{k,max}/T_{k,max}\right)^{(2015)} \times \sigma \times R_k^{(2015)}$. The parameter

$R_k^{(2015)}$ is the ratio of embodied-to-(maximum) operational energy for the k^{th} class of equipment (referring to Appendix A, Table A1) and σ is the typical lifetime of the k^{th} class of equipment. The ratio of embodied-to-operational energy of various telecom network equipment classes can also be found in [23] and [24]. It should be noted that in Eq. (17), the equipment units in class *k* should have the same *R*, and similar $\left(\eta_{k,embodied}\right)$.

2.3. Monte Carlo analysis

In this section, Monte Carlo simulation is used to estimate the current trends in energy efficiency improvements in both the operational and embodied phases, and the mean values, ranges, and probability distributions of the uncertainty parameters are discussed.

2.3.1. Monte Carlo simulation

Monte Carlo simulation is used to estimate the total network operational and embodied energy consumption from 2016 to 2025 given the uncertainty in the input parameters. The simulation is programmed using MATLAB. The simulation setup begins by choosing a random value for every input parameter that exhibits uncertainty based on the corresponding mean values, ranges, and probability distributions given in Table 1. The uncertainty parameters are: (1) annual reduction in network overhead power consumption ($\alpha_{o/h}$); (2) annual reduction in energy per bit of the network equipment (α_{max}); (3) annual reduction in baseline power of network equipment (α_{base}); (4) annual reduction in embodied energy efficiency of network equipment (α_{emb}); and (5) the network traffic growth rates. All input parameters are set to have the same number of decimal points: 4 decimal points so that the simulation results will not be affected by the different magnitudes in the accuracy of the input parameters. The input parameters are then inserted into the energy models presented in Sections 2.1 and 2.2 to generate estimates of the total network energy consumption (both operational and embodied energy) from 2016 to 2025. To obtain the results the process is repeated for 100,000 iterations. It should be noted that 100,000 iterations are chosen because the results show no difference beyond 50,000 iterations. To maintain the consistency in magnitude with input uncertainty parameters, all output parameters are set to 4 decimal points.

Table 1. The estimated mean values, ranges and probability distribution of all uncertainty parameters used in the Monte Carlo simulation to forecast the total network energy. Note: In the Monte Carlo simulation all input parameters are set to 4 decimal points.

Parameter	**Mean value**	**Range – three standard deviations**	**Distribution**	**Source**
Annual reduction in network overhead power consumption ($\alpha_{o/h,ave}$)	6.7%	2.09% – 10.95%	Custom (Normal distribution with skewness towards lower range)	[7, 21, 25]
Annual reduction in energy per bit of future network equipment (α_{max})	10%	-10% – 30%	Normal distribution	[26]
Annual reduction in baseline power of network equipment (α_{base})				
1. Baseline power that can be achieved in next generation equipment (P_{base_target})	45%	40% – 50%	Normal distribution	[27-29]
2. Year to achieve P_{base_target} commercially available (R_{year})	2020	2015 – 2025	Normal distribution	[21]
Annual reduction in embodied energy efficiency of network equipment (α_{emb})				
1. Annual reduction in production energy efficiency of semiconductors (α_{sem})	9.35%	6.85% – 11.85%	Normal distribution	[22]
2. Annual reduction in production energy efficiency of steel (α_{steel})	2%	1.6% – 2.4%	Normal distribution	[32]
3. Production energy ratios of material composition	33% (semicon	24% – 42% (semiconductors)	Normal distribution	[8, 18, 31]

in next generation network equipment (ρ)	ductors) 31% (steel)	14% – 48% (steel)		
Annual network traffic growth rates	Refer to medium traffic growth rates in Table 3	Minimal scenario = low traffic growth rates in Table 3 for each year; maximal scenario = high traffic growth rates in Table 3 for each year	Custom (Normal distribution with skewness for the given three standard deviation values)	[1]

2.3.2. *Annual reduction in network overhead power consumption ($\alpha_{o/h}$)*

In the minimal scenario, we assume a yearly reduction of 2.09% based on the historical data of PUE reduction for global data centers from 2005 to 2020, given by [7]. In the average scenario, we assume a yearly reduction of 6.7% based on the prediction from [21] for which the PUE of telecommunication networks is expected to reduce from 2.0 to 1.5 from 2010 to 2020. In the maximal scenario, we assume a yearly reduction of 10.95% in overhead power consumption based on historical PUE data from Google [25].

2.3.3. *Annual reduction in energy per bit of network equipment (α_{max})*

In the average scenario, we assume a 10% reduction in energy per bit of future network equipment based on the results from [26]. The minimal and maximal scenarios are extrapolated from the historical data of yearly reduction in energy per bit compared to previous generation equipment (referring to Appendix A, Fig. A1). We found that the variations in reducing the energy per bit of network equipment from post-2000 tend to become smaller, i.e., between -10% (which indicates an increase in energy per bit of the equipment by 10%) and 30% compared to prior 2008 [26]. This is because next generation network equipment could be designed to address capacity, quality-of-service and other requirements, not necessarily for energy efficiency. Therefore, we assume the minimal and maximal scenarios of -10% and 30%, respectively, for the reductions in equipment annual energy per bit of next generation network equipment.

2.3.4. *Annual reduction in baseline power of network equipment (α_{base})*

Two uncertainty parameters are relevant in determining the annual reduction in baseline power of the network equipment. First, we determine the baseline power consumption that can be achieved in next generation network equipment. Second, we determine the year in which this technology will be available.

In [27-29], several energy saving techniques have been evaluated using different network topologies. In general, the baseline power consumption of a network can be reduced by 50% to 60%. Therefore, for the baseline power that can be achieved in next generation network equipment, we assume an average scenario of 45% with the minimal and maximal scenarios of 40% to 50%, respectively.

Next, we predict the year in which the network equipment with the above energy savings technology will be commercially available. According to [21], the network equipment with energy-efficient technologies is expected to be commercially available in 2020. Therefore, in the average scenario, we assume that network equipment with the targeted baseline power consumption will be available in 2020 with the minimal and maximal scenarios of 2015 and 2025, respectively.

In each iteration of the Monte Carlo simulation, a value for the achievable equipment baseline power, (P_{base_target}) will be chosen randomly based on a probability distribution, mean value, and range given above and shown in Table 1. Hence, a random year will be chosen (R_{year}) in which the network equipment with P_{base_target} will be available. R_{year} is randomly chosen based on the mean value, range, and probability distribution shown in Table

1. Then the following formula is used to determine the annual reduction in baseline power of next generation network equipment:

$$\alpha_{base} = 1 - \left(\frac{P_{base\_target}}{P_{base\_2015}}\right)^{\left(1/(R_{year}-2015)\right)}. \quad (18)$$

2.3.5. *Annual reduction in embodied energy efficiency of network equipment (α_{emb})*

There are three uncertainties in determining the annual reduction in embodied energy efficiency of new network equipment: 1) annual reduction in production energy efficiency of semiconductors (α_{sem}); 2) annual reduction in production energy efficiency of steel (α_{steel}); and 3) production energy ratio of material composition in next generation network equipment. It should be noted that α_Y is the annual fractional reduction in production energy efficiency of parameter Y between year τ and τ+1 (refer to Eq. (8)). α_{emb} can be determined using the following formula:

$$\alpha_{emb} = (\alpha_{sem} \times \rho_{sem}) + (\alpha_{steel} \times \rho_{steel}) + (\alpha_{others} \times \rho_{others}), \quad (15)$$

where α_{others} represents the annual reduction in production energy consumption of other components and/or other life cycle stages (e.g., printed circuit boards, bulk material, maintenance, supply chain, etc.). In this paper, we apply a minimum annual energy efficiency improvement for α_{others}. ρ_{sem} is the production energy ratio of semiconductors (which is defined as the ratio of the contribution of total production energy of network equipment due to semiconductors to the total production energy of the network equipment). Likewise, ρ_{steel} and ρ_{others}, are the production energy ratios of steel and other components in network equipment.

2.3.5.1. Annual reduction in production energy efficiency of semiconductors (α_{sem})

The annual reduction forecast in production energy efficiency of semiconductors is derived from [22] (referring to Appendix A, Fig. A2). The International Roadmap for

Semiconductors (ITRS) provides detailed information on projected semiconductor chip technology from 2011 to 2022, as well as information on chip size, chip performance, and chip manufacturing energy [22]. We collected the following information from ITRS: projected number of transistors per chip area in cm^2, projected chip clock frequency, and projected chip production energy consumption per area in cm^2. Using these parameters, we calculated the production energy consumption per clock frequency (kWh/GHz) from 2011 to 2022.

As discussed in Section 2.2, the embodied energy efficiency, $\eta_{embodied}$ is defined as the embodied energy required for producing, deploying and decommissioning a network element with maximum capacity, T_{max}. Therefore, embodied energy efficiency has a functional unit of joules/(bits per second) or Wh/(bits per second). However, the production energy efficiency of semiconductors is measured at Wh/GHz [22]. The relationship between speed and bandwidth is given in [30]. The speed of the detector of a device can be illustrated as the time it takes to convert an input signal into an output signal. However, how fast the detector output responds to a change in the input signal is dependent on the rise time or bandwidth [30]. The bandwidth of a detector is defined as the frequency at which the output signal has dropped to 3dB (50%) below the power at a low frequency [30]. The 3-dB bandwidth can be estimated from the rise time using the formula (0.35/Rise time) [30]. For relatively slow devices, the rise time is proportional to the photodiode capacitance multiplied by the sum of the load resistance and the diode's internal resistance [30]. Therefore, reducing the equivalent capacitance can increase the speed of the device. For devices with higher speeds, the speed is further dependent on the diffusion of current carriers and the time needed for carriers to cross the depletion region of the semiconductor [30].

Given the above relationship between the speed and the bandwidth of a device, we determine that the annual reduction in Wh/GHz for semiconductors can be applied to network equipment with a functional unit of Wh/(bits per second). In the average scenario, the reduction in production energy efficiency of semiconductors is 9.35% per year and we assume the minimal and maximal scenarios of ±2.5% of mean value.

2.3.5.2. *Annual reduction in production energy efficiency of steel (α_{steel})*

A major part of the embodied energy of the network equipment is in the steel used to fabricate the frames and racks in which the electronics are housed [31]. Based on [32] (which is the historical data of production energy efficiency of steel in the U.S. from 1995 to 2010), we found a mean value of 2% annual reduction in production energy efficiency of steel (British thermal unit/ton) in the U.S. from 1990 to 2010, and the 95% confidence interval is ± 0.4% of the mean value.

2.3.5.3. *Production energy ratio of material composition in next generation network equipment (ρ_{sem}, ρ_{steel}, and ρ_{others})*

The production energy ratio of material composition in different types of network equipment varies as shown in Table 2. Based on data provided by [8, 18, 31], we assume that the mean values for the production energy ratio of semiconductors (ρ_{sem}) and steel (ρ_{steel}) are 33% and 31%, respectively. The minimal and maximal scenarios away from the mean values for the production energy ratios are ±9% for semiconductors and ±17% for steel, respectively. This gives a maximal scenario in which the distributions of production energy ratios for semiconductors, steel, and other items in an equipment unit are 42%, 48%, and 10%, respectively.

Table 2. Production energy of material composition in various network equipment types. The data are derived from multiple sources shown in the table.

Ref-erence	Equipment Type	PCB	Semi-conductors	Bulk Material	Steel	Main-tenance	Others
[31]	Core router	1.01%	12.92%	7.35%	68.72%	10.00%	Not reported
	Optical switch	1.81%	33.75%	9.84%	44.60%	10.00%	Not reported
[18]	Server	33.51 %	27.68%	1.47%	21.63%	Not reported	5.72%
	Switch	26.74 %	48.59%	0.73%	11.91%	Not reported	2.26%
[8]	Mobile base station	5.00%	44.00%	7.00%	8.00%	12.00%	24.00%

2.3.6. Network traffic growth rates

We compared the network traffic growth rates given by [1, 2, 19]. The compound annual growth rates (CAGR) given by [19] are too aggressive and both [2] and [19] did not provide any explanations for the methods used to justify the CAGR given in those articles. In contrast, [1] provides a clear explanation on how to estimate the CAGR. Linearized regression analyses of a combination of historical and nearer-term traffic forecasts have been carried out to project macroscopic future Internet traffic for several geo-economic regions, market segments, and application categories using a semi-empirical hyperbolic function [1]. The network traffic growth rates from 2016 to 2025 are represented for low, medium and high as shown in the Table 3. In the Monte Carlo simulation, we assume the average scenarios in annual traffic growth rates as the medium CAGR shown in Table 3 and the minimal and maximal scenarios are as the low and high CAGR in Table 3, respectively.

Table 3. Compound annual network traffic growth rates derived from [1].

Year	Compound annual growth rate (CAGR)		
	Low	**Medium**	**High**
2016	23.90%	29.36%	32.55%
2017	21.83%	27.70%	30.91%
2018	19.95%	26.20%	29.38%
2019	18.24%	24.84%	27.95%
2020	16.68%	23.59%	26.61%
2021	15.18%	22.41%	25.28%
2022	13.81%	21.29%	24.01%
2023	12.57%	20.23%	22.81%
2024	11.44%	19.22%	21.67%
2025	10.41%	18.26%	20.59%

2.4. Collection of real network data

Network data of the California Research and Education Network (CalREN) are used to demonstrate the results in this paper. The complete network data are shown in the Appendix B. Because network information from commercial networks is proprietary and therefore very difficult to obtain, we use network information from CalREN for two reasons: the information (1) is publicly available; (2) consists of fine-grained network traffic data and equipment model information. Furthermore, we found that the network equipment units of CalREN are similar to those of British Telecom global multiprotocol labelling switching (MPLS) networks. However, due to confidentiality of commercial network data, only CalREN network data will be used in this paper. The CalREN core network is a multitiered, advanced network services fabric serving the vast majority of research and education institutions in the state of California. The entire CalREN network consists of 43 nodes and it is expected to have an annual energy consumption of 1.23 GWh in 2015. All of the network equipment units have been grouped into three different classes of equipment, in which small class routers consumed approximately 0.05 GWh, medium class routers consumed approximately 0.91 GWh, large class routers consumed 0.27 GWh and the power usage effectiveness (PUE) values of all of the central offices that house the units are assumed to be

1.7 in the year 2015 [33]. The total network traffic load is approximately 180 Gbps and the traffic handled by small, medium and large classes of routers are 5%, 64% and 31%, respectively. The network topology of CalREN, full list of the equipment type and maximum equipment power consumption for the 43 nodes are listed in Appendix B.

3. Results and discussion

The aim of the paper is to study the interdependencies between (i) the energy efficiency improvements (e.g., new emerging technology) in terms of operational and embodied phases, (ii) the equipment replacement cycle, and (iii) the network traffic growth and the resulting growth in network operational and embodied energy consumption of a network. Although the model developed here could be used to estimate the energy consumption of future networks, it is not the aim of the paper because the energy consumption of a network could vary significantly depending on (i), (ii), and (iii).

3.1. Analyzing the operational and embodied energy of a rapidly growing network

One major challenge in managing the sustainable growth of a network is to decide the equipment replacement strategy, which could result in the lowest total network energy consumption. Traditionally, the timing of replacing legacy network equipment is purely based on the financial decision instead of the environmental impact of the network. However, because of the increasing importance in fulfilling the corporate's environmental and social responsibilities, managing the network life cycle energy and the associated environmental impact has become extremely important for network operators. Therefore, the results shown here will be valuable for network operators wishing to better manage the total life cycle energy of their networks in the future while considering the underlying capital investment requirements.

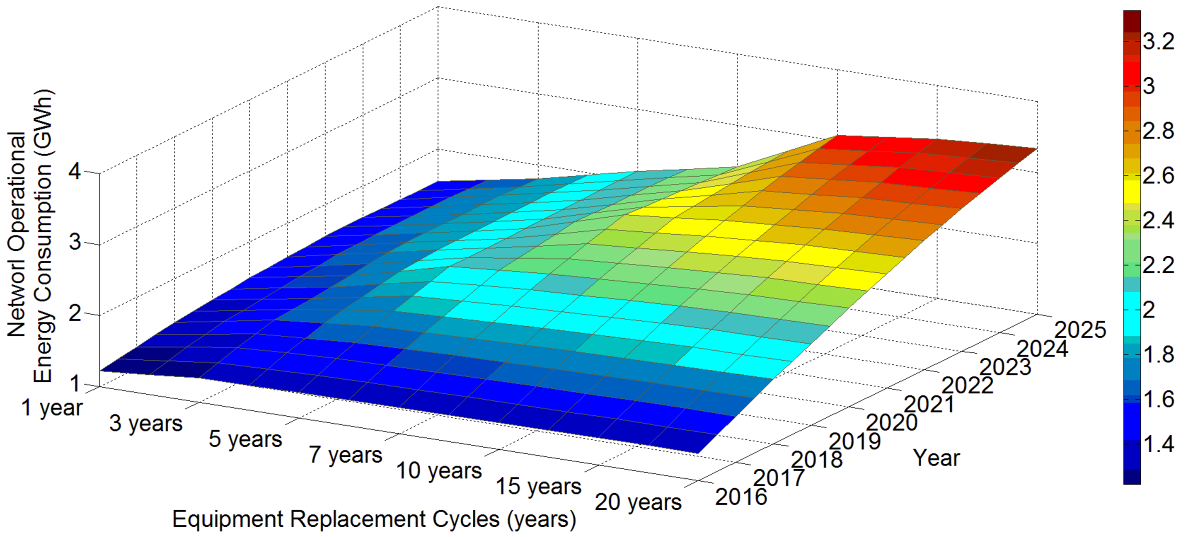


Fig. 1. Network operational energy consumption under different network equipment replacement cycles and the current trends of network operational energy efficiency improvements. Note: For the 95% confidence intervals of the mean values refer to Appendix A, Table A2.

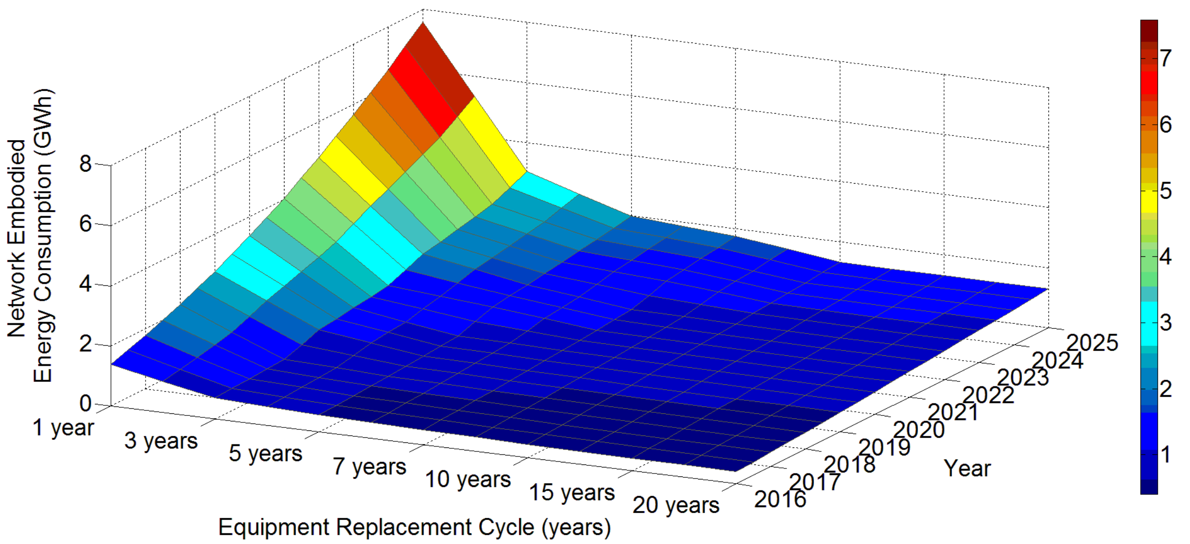


Fig. 2. Network embodied energy consumption under different network equipment replacement cycles and the current trends of network embodied energy efficiency improvements. Note: For the 95% confidence intervals of the mean values refer to Appendix A, Table A3.

Here, we investigate the impact of different network equipment replacement cycles on the resulting operational and embodied energy due to future network traffic growth. Figs. 1 and 2 show the estimated network operational and embodied energy consumption of CalREN, respectively, from 2016 to 2025 under different equipment replacement cycles. The results are generated using the Monte Carlo simulation discussed in Section 2.3.1.

Intuitively, long equipment replacement cycle will increase the total network operational energy consumption in the future because legacy network equipment tends to have poorer energy efficiency compared to the state-of-the-art network equipment. However, the benefit of a longer equipment replacement cycle is lower network embodied energy required because fewer equipment units will be deployed in the network every year compared to a shorter equipment replacement cycle. In contrast, a short equipment replacement cycle could decrease the total network operational energy due to frequent replacement of legacy equipment with more energy-efficient equipment in the network. However, a shorter equipment replacement cycle tends to increase the network embodied energy (i.e., energy used in raw material acquisition and pre-processing, production, distribution, and end-of-life treatment of network equipment and devices) due to the decommissioning of a large number of equipment units and their replacement with state-of-the-art equipment.

Under the current trends in energy efficiency improvements (as determined by the Monte Carlo simulation described in Section 2.3.1), the operational and embodied energy of the network is expected to increase significantly from 2016 to 2025 as shown in Figs. 2 and 3. This means that in order to meet the future demand of network traffic growth, higher energy efficiency improvements in both operational and embodied phases are required to maintain the sustainable growth of the network. Further, the ratio of network embodied energy to the total network energy consumption for equipment replacement cycles of 20 years to 3 years will increase from a range of 23% (± 0.05%) to 34% (± 1%) in 2016 to a range of approximately 28% (± 1%) to 63% (± 7%) in 2025. This increase is primarily due to the slow energy efficiency improvement per year for the embodied energy. It should be noted that the simulation results show that as the equipment replacement cycles decrease from 20 years to 3 years, the range of the 95% confidence intervals to the mean values increases due to more equipment units being replaced, and thus increases the uncertainties. Also, as the number of forecast years increases from 2016 to 2025, the range of the confidence intervals to the mean values will also increase due to the increases in the uncertainties.

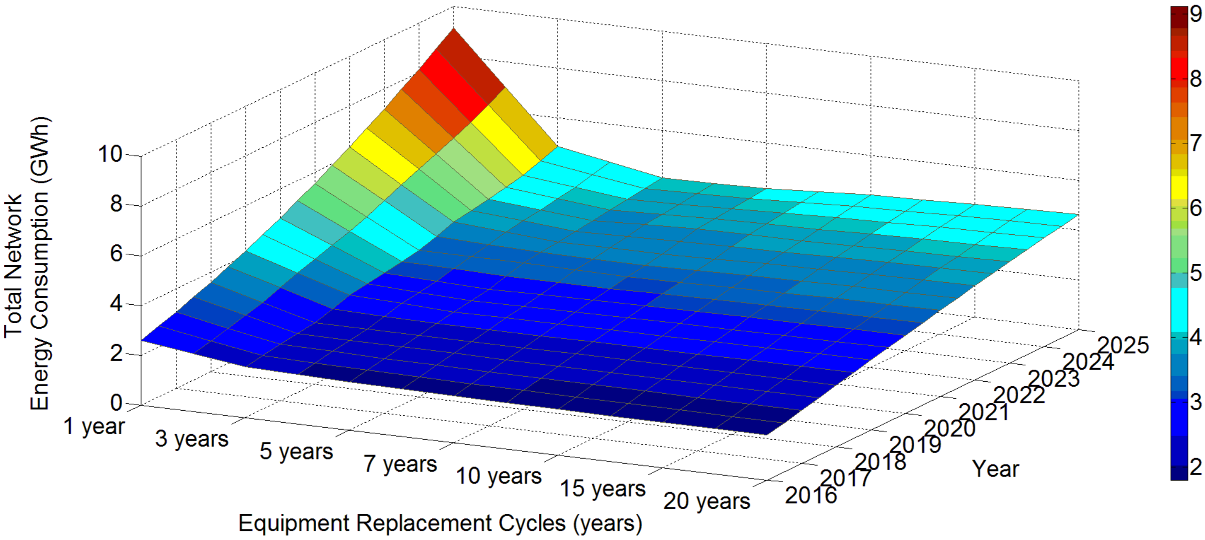


Fig. 3. Total network energy consumption under current trends of energy efficiency (in both operational and embodied) improvements. Note: For the 95% confidence intervals of the mean values refer to Appendix A, Table A4.

By combining the impacts of network operational energy (Fig. 1) and embodied energy (Fig. 2), Fig. 3 shows the total network energy consumption under current trends of energy efficiency improvement in both operational and embodied phases. Here, we define the optimal equipment replacement cycle as the equipment replacement frequency, which will result in the lowest network energy consumption in terms of both operational and embodied phases. As shown in Fig. 3, the optimal equipment replacement cycle is between 5 years to 10 years under current trends in energy efficiency improvements and network traffic growth. However, the optimal equipment replacement cycle could vary depending on the variations in network traffic growth rates and the technological progress in energy efficiency improvements.

3.2. Meeting the energy demand of future network traffic growth

Meeting the energy demand of rapid growth in network traffic has become a major challenge for network operators. Fig. 4 shows the total energy consumption of the network and the ratio of embodied energy to the total network energy of CalREN by 2025 as a function of different traffic compound annual growth rates (CAGRs) of the network. The grey region shows the current trends of network traffic growth rates (95% confidence intervals) modeled using the Monte Carlo simulation described in Section 2.3.1. Intuitively, as the CAGR of network traffic increases, more network equipment units need to be deployed in the network and hence increasing the network operational energy consumption exponentially. Under current trends in energy efficiency improvements (referring to Section 2.3), the ratio of embodied energy to the total network energy will increase as the CAGR of network increases. This is primarily due to the slow energy efficiency improvement per year for the embodied energy.

Traditionally, the total life cycle energy consumption of a network is always dominated by the operational energy as shown by [8, 16, 23]. As a consequence, the energy used to build the network (i.e., embodied energy) has always been overlooked. The results shown in Fig. 4 suggest that *if no additional research efforts are made to improve the energy efficiency of network embodied energy, the network embodied energy will eventually dominate the total network life cycle energy in the future*. This issue will become crucial in the sustainability management of a network, which could potentially shift the focus from operational energy to embodied energy.

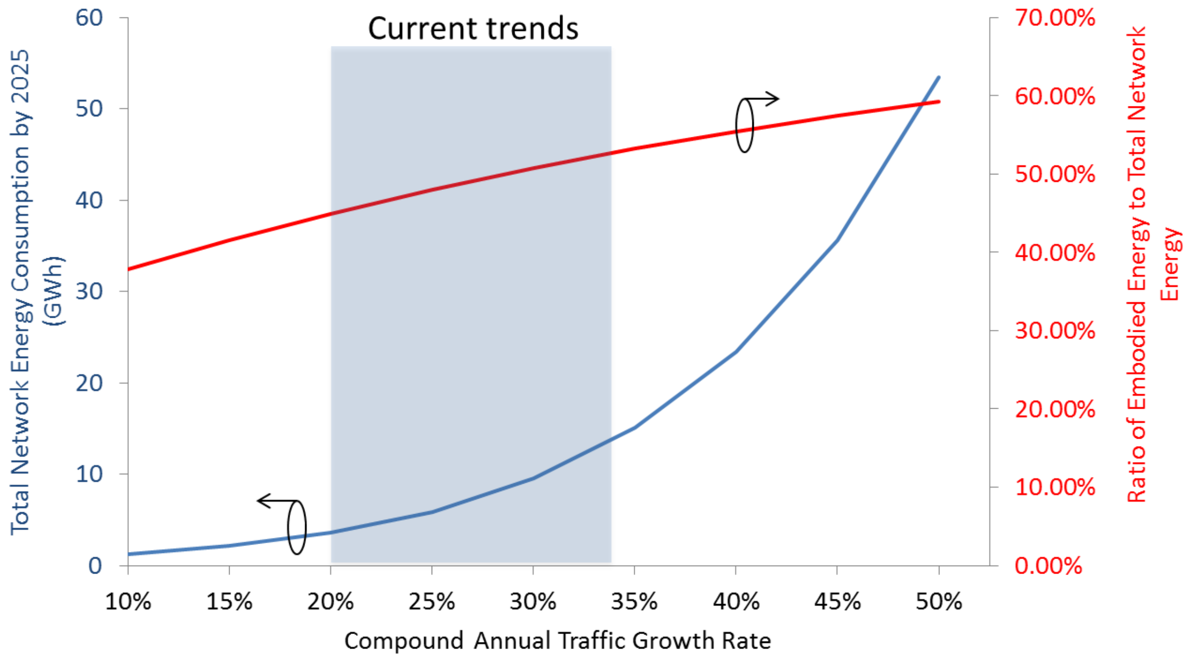
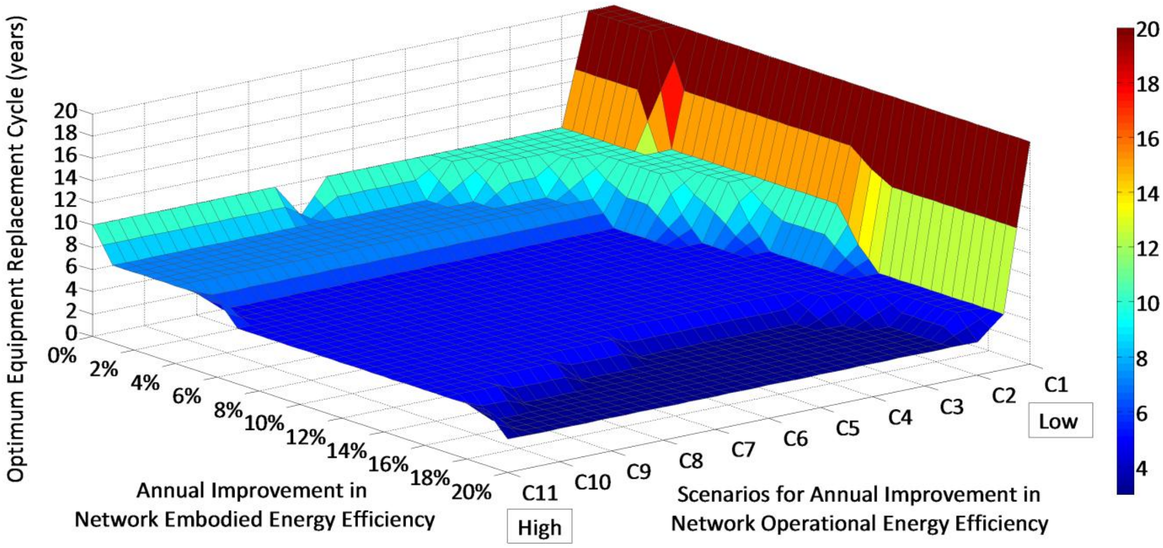


Fig. 4. Total energy consumption and the ratio of embodied energy to total network energy by 2025 against different compound annual traffic growth rates.

To manage the sustainable growth of a network without constraining the network traffic growth, the most straightforward ways are the followings: (i) improve the energy efficiency of both operational and embodied, and (ii) deploy network equipment at the optimal equipment replacement cycle, which could result in the lowest total energy consumption.

3.3. Impact of energy efficiency improvements on equipment replacement cycle

To better manage the energy consumption of a growing network, the network operator has to make the decision on when to replace the old network equipment units in their network to gain operational energy efficiency improvements. However, different embodied and operational energy efficiency improvement rates could potentially impact this decision. For example, as the energy efficiency improvement in the embodied phase increases, the optimal equipment replacement cycle will be shorter because lower embodied energy promotes more rapid equipment replacement. The terms 'optimal equipment replacement cycle' refers to the equipment replacement cycle that will result in the lowest total network energy consumption (in terms of both operational and embodied energy). Fig. 5 shows a sensitivity analysis of the optimum network equipment replacement cycle over the period of 2016 to 2025, given different annual operational and embodied energy efficiency improvement rates of the network equipment. Referring to the energy models in Section 2.1, the annual network operational energy efficiency improvement consists of three important factors: (i) annual reduction in network overhead power consumption ($\alpha_{o/h,ave}$), (ii) the annual reduction in energy per bit of future network equipment (α_{max}), and (iii) the annual reduction in baseline power of network equipment (α_{base}). In the sensitivity analysis, the range of values for $\alpha_{o/h,ave}$, α_{max}, and α_{max} are defined in the box in Fig. 5 for each annual improvement scenario in network operational energy efficiency (i.e., C1 to C11). By including $\alpha_{o/h,ave}$, α_{max}, and α_{max} into the energy models, the effective annual operational energy efficiency improvement rates of the network can be calculated for C1 to C11 (referring to Eq (7)) and are shown in Table 4. The effective annual energy efficiency improvement rates of the network takes into account a greater increase in peak traffic compared with the average traffic as forecasted by [2] and different equipment replacement cycles.



Scenarios for Annual Improvement in Network Operational Energy Efficiency	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
Annual reduction in network overhead power consumption ($\alpha_{o/h,ave}$)	0%	1.7%	3.4%	5.1%	6.8%	8.5%	10.2%	11.9%	13.6%	15.3%	17.0%
Annual reduction in energy per bit of future network equipment (α_{max})	0%	1.7%	3.4%	5.1%	6.8%	8.5%	10.2%	11.9%	13.6%	15.3%	17.0%
Annual reduction in baseline power of network equipment (α_{base})	0%	1.0%	2.0%	3.0%	4.0%	5.0%	6.0%	7.0%	8.0%	9.0%	10.0%

Fig. 5. The plot shows the optimum equipment replacement cycle (which will result in the lowest total network energy consumption between 2016 to 2025) as a function of equipment energy efficiency improvements in terms of operational and embodied phases. The table shows the values of annual reduction in network overhead power consumption ($\alpha_{o/h,ave}$), the annual reduction in energy per bit of future network equipment (α_{max}), and the annual reduction in baseline power of network equipment (α_{base}) for each annual improvement scenario in network operational energy efficiency (i.e., C1 to C11).

Table 4. Effective annual energy efficiency improvement of the network (%) for different annual improvement scenarios in network operational energy efficiency improvement. Negative values indicate reduced energy efficiency.

Scenarios for annual improvement in network operational energy efficiency	**Equipment replacement cycle**						
	1 year	**3 years**	**5 years**	**7 years**	**10 years**	**15 years**	**20 years**
C1	-3.27%	-3.27%	-3.27%	-3.27%	-3.27%	-3.27%	-3.27%
C2	-0.39%	-0.64%	-0.89%	-1.04%	-1.33%	-1.38%	-1.40%
C3	2.75%	2.25%	1.77%	1.44%	0.84%	0.74%	0.69%
C4	7.12%	6.37%	5.66%	5.16%	4.23%	4.06%	3.97%
C5	10.27%	9.31%	8.39%	7.63%	6.33%	6.08%	5.95%
C6	13.83%	12.66%	11.49%	10.62%	8.88%	8.52%	8.35%
C7	16.09%	14.71%	13.29%	12.21%	10.12%	9.69%	9.48%
C8	18.99%	17.40%	15.81%	14.52%	12.02%	11.48%	11.22%
C9	22.04%	20.24%	18.41%	16.92%	13.90%	13.22%	12.90%
C10	24.30%	22.31%	20.16%	18.47%	15.16%	14.37%	13.99%
C11	27.21%	25.05%	22.69%	20.73%	17.01%	16.03%	15.58%

As shown in Fig. 5, the replacement of old equipment units is not necessary if the annual operational energy efficiency improvement of the network is close to 0% (network traffic growth outweighs the technological progress in operational energy efficiency improvement of the equipment) because new units will not perform any better compared to old units in terms of operational energy efficiency. As the annual network operational energy efficiency improvement increases from C1 to C11, the optimum equipment replacement cycle reduces because replacing old equipment with new units could now reduce the total network operational energy consumption. However, in the scenarios where the annual embodied energy efficiency improvement of the network is significantly less than the annual operational energy efficiency improvement, the embodied energy consumption of the network becomes dominant and hence restricts further reductions in the operational energy of the network through a shorter equipment replacement cycle. As a result, the optimal equipment replacement cycle requires a balance between the embodied and operational energy efficiency improvements.

Our results show that although current major research efforts in improving the operational energy efficiency are important, a focus on embodied energy is also essential for networks to become sustainable in the long term. In other words, technological advances in both operational and embodied energy efficiency should be achieved hand-in-hand in order to make future telecommunication networks sustainable.

4. Conclusions

The findings in this paper demonstrate the interdependencies of the four contributing factors in managing the energy consumption of a growing telecommunications network: (i) the network's operational energy consumption; (ii) the embodied energy of network equipment; (iii) network traffic growth; and (iv) energy efficiency improvements in both the operational and embodied phases. Using Monte Carlo simulation and real network data collected from a state-wide research and education network, we demonstrated how the network operator's decision on equipment replacement frequency could affect the resulting network operational and embodied energy consumption in the future. Further, we demonstrated how network traffic growth rates could impact the resulting operational and embodied energy consumption of the network. Traditionally, the network operational energy represents the dominant component of the entire network life cycle energy. Therefore, the network embodied energy has always been overlooked by network operator. In this paper, we found that the contribution of network embodied energy as a ratio of the total network energy, is expected to increase significantly in the future. This issue will become more severe as the network traffic growth increases due to slow energy efficiency improvement per year for the embodied energy. Therefore, in future work one would wish to perform a more detailed analysis and model the individual life-cycle stages within the network embodied energy component to determine the dominating factors. Further, we investigated the interdependencies of energy efficiency improvements in both operational and embodied energy and the optimum equipment replacement strategy for better managing the energy consumption of a growing network. Our results showed that intensive research efforts in improving the energy efficiency of one area alone may not be sufficient in achieving the goal of sustainability. Although improving operational energy efficiency is a worthy goal in terms of reducing the energy costs of the network, a focus on embodied energy is also essential for networks to become sustainable in the long term.

Acknowledgements

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Appendix A. Uncertainty parameters and 95% confidence intervals of the results

Equipment class	**Typical lifetime**	**Lifetime cycle stage ratio**	
		Operational	**Embodied**
Router – small chassis/blade (2 slots)	10 years	85%	15%
Router – medium chassis/blade (3 – 6 slots)		85%	15%
Router – large chassis/blade (9 + slots)		95%	5%
Router – core		90%	10%
Switch – small chassis/blade (2 slots)	15 years	85%	15%
Switch – medium chassis/blade (3 – 6 slots)		85%	15%
Switch – large chassis/blade (9+ slots)		95%	5%
Switch – enterprise		90%	10%

Table A1. Life cycle embodied-to-operational energy ratio for different classes of routers and switches in 2015 [23]. The ratios for different types of network equipment units such as the server, the digital subscriber line (DSL) gateway, the passive optical network (PON) gateway, the home gateway, the mobile wireless gateway, the base station, etc. can be found in [23].

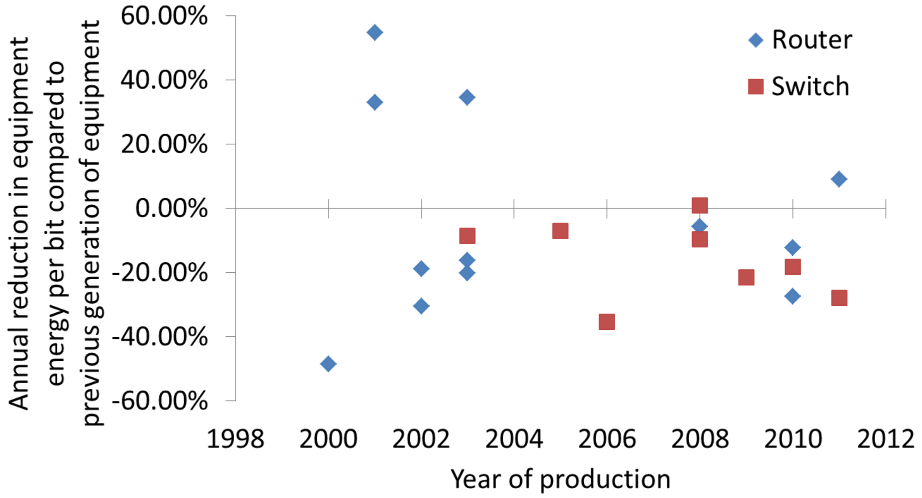

Fig. A1. Annual reduction in equipment energy per bit compared to previous generation of equipment for routers and switches. The data points are derived from [26].

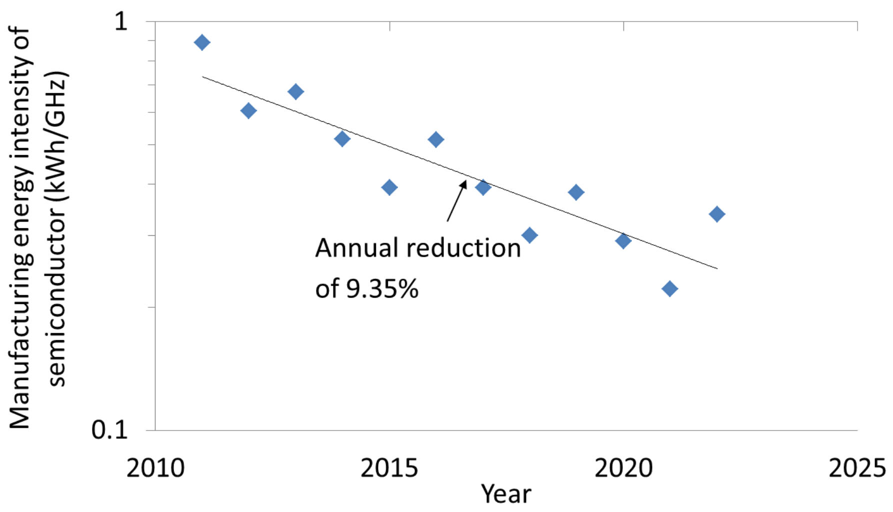

Figure A2. Manufacturing energy intensity of semiconductors derived from [22]. The trend shows an average annual reduction of 9.35% with 95% confidence interval of ±2.5% of mean value.

Year	Equipment replacement cycles						
	1 year	3 years	5 years	7 years	10 years	15 years	20 years
2016	-12.5% to 12.7%	-6.2% to 6.6%	-5.2% to 5.6%	-4.8% to 5.2%	-4.5% to 4.9%	-4.3% to 4.6%	-4.2% to 4.6%
2017	-17.8% to 19.0%	-11.3% to 11.9%	-9.1% to 9.6%	-8.3% to 8.8%	-7.7% to 8.1%	-7.2% to 7.7%	-7.0% to 7.5%
2018	-22.1% to 24.4%	-16.3% to 17.5%	-12.9% to 13.9%	-11.7% to 12.5%	-10.7% to 11.5%	-10.0% to 10.8%	-9.7% to 10.5%
2019	-25.7% to 28.6%	-21.2% to 23.4%	-16.4% to 17.8%	-14.7% to 16.0%	-13.5% to 14.8%	-12.6% to 13.8%	-12.2% to 13.3%
2020	-29.0% to 33.0%	-24.8% to 27.8%	-19.8% to 21.5%	-17.5% to 19.3%	-16.0% to 17.6%	-14.9% to 16.5%	-14.3% to 15.9%
2021	-31.9% to 37.4%	-28.1% to 32.0%	-24.2% to 27.0%	-20.2% to 22.2%	-18.4% to 20.2%	-17.1% to 18.9%	-16.4% to 18.2%
2022	-34.5% to 41.6%	-31.3% to 36.7%	-27.8% to 31.9%	-22.7% to 25.7%	-20.6% to 23.3%	-19.2% to 21.6%	-18.5% to 20.8%
2023	-36.8% to 45.1%	-34.3% to 40.6%	-31.0% to 36.5%	-26.7% to 30.9%	-22.6% to 25.9%	-20.9% to 24.1%	-20.1% to 23.2%
2024	-38.8% to 48.6%	-36.3% to 44.0%	-33.5% to 40.1%	-30.0% to 35.2%	-24.6% to 28.6%	-22.7% to 26.5%	-21.8% to 25.5%
2025	-41.0% to 51.0%	-38.4% to 47.7%	-35.7% to 43.1%	-32.6% to 39.3%	-26.4% to 31.0%	-24.2% to 28.5%	-23.2% to 27.4%

Table A2: 95% confidence intervals for the mean values in Figure 1.

Year	Equipment replacement cycles						
	1 year	3 years	5 years	7 years	10 years	15 years	20 years
2016	-3.3% to 3.4%	-6.5% to 6.6%	-8.0% to 8.2%	-9.0% to 9.2%	-9.9% to 10.1%	-10.7% to 10.9%	-11.1% to 11.4%
2017	-4.7% to 4.9%	-8.0% to 8.3%	-9.6% to 10.0%	-10.6% to 11.0%	-11.4% to 11.9%	-12.2% to 12.7%	-12.6% to 13.1%
2018	-5.8% to 6.0%	-9.3% to 9.7%	-11.0% to 11.4%	-11.9% to 12.4%	-12.7% to 13.2%	-13.4% to 14.0%	-13.8% to 14.3%
2019	-6.8% to 7.1%	-9.4% to 9.9%	-12.8% to 13.3%	-13.7% to 14.3%	-14.5% to 15.1%	-15.2% to 15.8%	-15.5% to 16.2%
2020	-7.6% to 8.1%	-10.8% to 11.6%	-14.3% to 15.4%	-15.1% to 16.3%	-15.9% to 17.1%	-16.5% to 17.8%	-16.8% to 18.1%
2021	-8.3% to 8.9%	-11.8% to 12.2%	-13.0% to 13.0%	-16.4% to 16.8%	-17.1% to 17.5%	-17.6% to 18.0%	-17.9% to 18.3%
2022	-9.1% to 9.6%	-11.7% to 12.6%	-14.2% to 14.7%	-18.1% to 18.9%	-18.8% to 19.5%	-19.3% to 20.0%	-19.6% to 20.3%
2023	-9.8% to 10.3%	-12.7% to 13.5%	-15.2% to 15.2%	-16.4% to 16.5%	-20.1% to 20.2%	-20.6% to 20.7%	-20.9% to 21.0%
2024	-10.4% to 10.9%	-13.4% to 14.3%	-15.8% to 16.8%	-16.9% to 17.6%	-20.8% to 21.7%	-21.2% to 22.2%	-21.5% to 22.4%
2025	-10.7% to 11.6%	-13.3% to 14.3%	-17.0% to 17.3%	-17.8% to 17.8%	-22.2% to 22.1%	-22.6% to 22.5%	-22.8% to 22.8%

Table A3: 95% confidence intervals for the mean values in Figure 2.

Year	Equipment replacement cycles						
	1 year	3 years	5 years	7 years	10 years	15 years	20 years
2016	-7.6% to 7.7%	-6.3% to 6.6%	-6.0% to 6.3%	-5.9% to 6.3%	-5.9% to 6.2%	-5.8% to 6.1%	-5.8% to 6.1%
2017	-10.2% to 10.9%	-10.2% to 10.7%	-9.3% to 9.8%	-8.9% to 9.4%	-8.6% to 9.1%	-8.4% to 8.9%	-8.3% to 8.8%
2018	-12.0% to 13.0%	-13.9% to 14.9%	-12.4% to 13.2%	-11.7% to 12.4%	-11.2% to 11.9%	-10.8% to 11.5%	-10.6% to 11.3%
2019	-13.3% to 14.5%	-16.2% to 17.7%	-15.4% to 16.5%	-14.4% to 15.6%	-13.7% to 14.9%	-13.2% to 14.3%	-12.9% to 14.0%
2020	-14.2% to 15.8%	-18.6% to 20.6%	-18.2% to 19.7%	-16.9% to 18.4%	-16.0% to 17.5%	-15.3% to 16.8%	-14.9% to 16.4%
2021	-14.8% to 16.7%	-20.5% to 22.9%	-20.0% to 21.7%	-19.1% to 20.7%	-18.0% to 19.5%	-17.2% to 18.7%	-16.8% to 18.3%
2022	-15.3% to 17.4%	-21.0% to 24.0%	-22.3% to 24.9%	-21.4% to 23.7%	-20.1% to 22.3%	-19.2% to 21.2%	-18.7% to 20.7%
2023	-15.6% to 17.8%	-22.3% to 25.6%	-24.2% to 27.3%	-22.9% to 25.7%	-21.9% to 24.3%	-20.8% to 23.2%	-20.3% to 22.6%
2024	-15.8% to 18.1%	-23.0% to 26.8%	-25.4% to 29.4%	-24.8% to 28.3%	-23.5% to 26.6%	-22.3% to 25.3%	-21.7% to 24.6%
2025	-15.8% to 18.2%	-22.6% to 26.7%	-26.7% to 30.7%	-26.4% to 30.3%	-25.1% to 28.3%	-23.8% to 26.8%	-23.1% to 26.1%

Table A4: 95% confidence intervals for the mean values in Figure 3.

Appendix B. Network data of CalREN collected from 2015

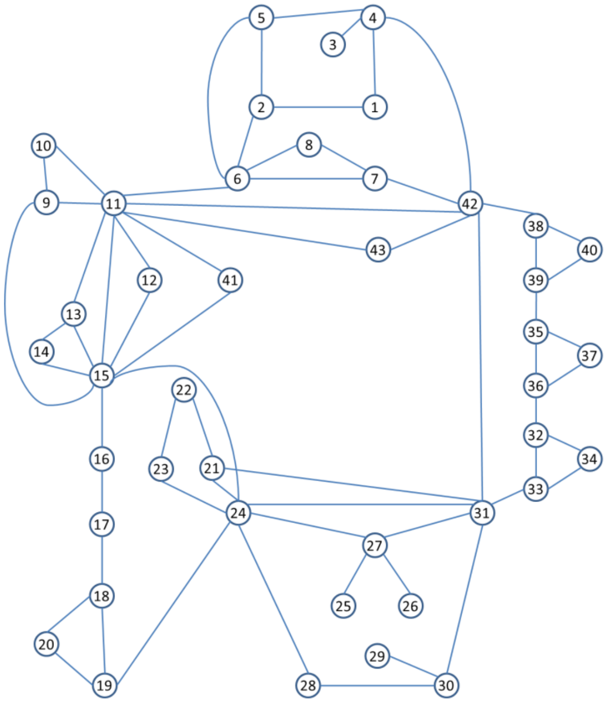

Figure B1: Network topology of CalREN [34].

Node number	Equipment type	Maximum equipment power (W)	Node number	Equipment type	Maximum equipment power (W)
1	Cisco 12410	1,715	23	Cisco 7204VXR	278
2	Cisco 12410	1,203	24	Cisco ASR9K10	4,370
3	Cisco 7206VXR	278	25	Cisco 12410	2,879
4	Cisco ASR9K06	1,089	26	Cisco 12410	2,995
5	Cisco ASR9K06	1,089	27	Cisco ASR9K06	2,554
6	Cisco 12410	2,995	28	Cisco 12410	2,995
7	Cisco 12410	2,995	29	Cisco 7206VXR	278
8	Cisco 7206VXR	278	30	Cisco ASR9K06	2,554
9	Cisco 12410	2,623	31	Cisco ASR9K10	3,510
10	Cisco 7204VXR	278	32	Cisco 7204VXR	278
11	Cisco ASR9K10	3,510	33	Cisco 12410	1,805
12	Cisco 12410	2,739	34	Cisco 12410	1,971
13	Cisco 12410	2,879	35	Cisco 12410	2,829
14	Cisco 7206VXR	278	36	Cisco 12410	1,715
15	Cisco ASR9K10	3,510	37	Cisco 7206VXR	278
16	Cisco 12410	1,971	38	Cisco 12410	2,317
17	Cisco 12410	1,715	39	Cisco 12410	2,739
18	Cisco 12410	1,971	40	Cisco 7206VXR	278
19	Cisco 12410	1,715	41	Cisco 12410	2,995
20	Cisco 7206VXR	278	42	Cisco ASR9K10	3,510
21	Cisco 12410	2,879	43	Cisco 12406	1,305
22	Cisco 7206VXR	278			

Table B1: Equipment power consumption list for CalREN. Node numbers are corresponding to Fig. B1. It should be note that, the power consumption values of two nodes with the same equipment model vary due to the use of different line card configurations. The power consumption values of different line cards are obtained from manufacturer website [35].

Equipment class	Equipment type	Total number of units	Total maximum power consumption for equipment type (W)	Total maximum power consumption per equipment class (W)
Small router class	Cisco 7206VXR	8	2,224	3,058
	Cisco 7204VXR	3	834	
Medium router class	Cisco 12406	1	1,305	61,231
	Cisco 12410	22	52,640	
	Cisco ASR9K06	4	7,286	
Large router class	Cisco ASR9K10	5	18,410	18,410
	Total	**57**	**82,699**	**82,699**

Table B2: Summary equipment list for CalREN. According to the network traffic data we collected with CalREN, the average network traffic for the entire network is approximately 180 Gbps. The network traffic portions for small router class, medium router class and large router class are 5%, 64% and 31%, respectively.

5. References

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